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TOOL WEAR MONITORING USING NNGE ALGORITHM

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ABSTRACT

Cutting tools are required to do the necessary machining operations in the manufacturing Industry. Continuous machining operation causes the tool to degrade. The machining operation done using a worn-out tool will have a poor surface finish. The poor surface finish undermines the accuracy of the component. This can be solved by using online system condition monitoring tools which helps in reducing the tool maintenance cost all the while increasing the productivity. This paper presents the classification performance of the Nearest-neighbour-like algorithm using non-nested generalized exemplar (NNge). A set of statistical data extracted from vibration signals for both good and faulty conditions form the input to the algorithm. In the present study, the NNge algorithm is able to achieve 100% classification accuracy.

KEYWORDS: Machine Learning, NNge, Tool Condition Monitoring & Vibration Signals

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Original Article

INTRODUCTION

The research on tool wear monitoring is becoming rapidly popular due to key reasons discussed by Jantunen (2002). Tool wear monitoring assures high productivity along with automation of the production line. For autonomous manufacturing system, it requires the ability to differentiate between developing, complete or disastrous malfunction conditions.

Surface finish and dimensional accuracy of the parts of the machine is linked to the tool condition. Conventionally the tool life is calculated from Taylor's tool life equation. It does not account for the complete life cycle of the tool. This does not enable us to predict the tool life with accuracy. It can overestimate the life of the tool or underestimate the life of the tool. Since the blunt tool can affect the surface finish, any underestimation of the tool life would force us to replace the tools excessively. It leads to excessive waste of time and resources. Rehorn (2004) showed that by increasing the cutting speed up to 50 % in using tool wear monitoring one can get up to 40 % return of investment. There are three stages in Tool wear monitoring. In the first stage, an appropriate monitoring strategy is identified. There are two different approaches used by monitoring strategies namely, direct and indirect approaches. Direct measurement of tool wear using optical method and statistical filtering as previously executed by Sortino (2003) comes under the direct approach. Jukovic (2004) developed a new approach to measure the tool condition using CCD. This method was improved to support online measurement by Lim, Son, Wong and Rahman (2007). Ozel and Karpat (2005) used roughness as a major factor to measure the tool wear. The data about the surface finish and tool flank wear obtained during hard turning. They used regression and neural networks on the dataset to predict tool wear. During implementation, good surface finish is requisite condition; Surface data acquisition becomes difficult and continuous online measurement is also not possible. This requires a technique which works well both in hard and soft turning. However, these direct methods are not accurate in all

conditions. In roughing operation when the cutting fluid surrounds the tool, continuous online measurement becomes difficult; therefore, due to these challenges in implementation, makes it economically unviable. This paper attempts to overcome these challenges.

The deformation of the tool in a very concentrated zone is due to changes in physical features like temperature due to tool condition as stated by Abukshim et al (2006). It is known that the heat generated during manufacturing causes deformations which affect both tool and work piece. Choudhury and Bartarya (2003) attempted to measure the temperature using thermocouple and use the data obtained for tool condition monitoring. This is influenced by factors such as environment like the changes in temperature and humidity, composition of the cutting fluid and thermal conductivity of the metal under study. This leads to changes in surface temperature. Therefore, the model will be required to be updated often which makes it difficult to be used onsite in the industry for tool wear monitoring. Tool wear also affects the cutting forces acting on tool-work piece interface which was used by Dimla and Lister (2000) and Gaoand Xu (2005). Lee et al (2007) identified later that dynamic force analysis was only suitable for a situation with a sudden and total failure of tools and not for tool wear. This deformation and variation in force intensity are used to generate a large number of signals which are used for online indirect monitoring.

Each signal has varied points of origin. Therefore, each signal has a different set of information in it. The blunter the tool, the more force is required for cutting operation. Therefore, the more effective and accurate method of analysis would be to measure the change in the current from the spindle of the servo motor (Lee et al. 2007; Franco-Gasca et al. 2006). Lee et al. (2007) developed a hybrid system after studying and analysing the effect the force component on the signals for tool wear monitoring. The hybrid systems required the use of sensors which would normally have been avoided due to the limitation of space and cost. Rotating machines are analysed by vibration. The strain energy and chipping at the work piece interface tends to generate acoustic emissions (Al-habaibeh & Gindy, 2001; Chen & Li, 2006; Srinivasa Pai, Naga bhushanab, & Rao, 2012) and ultrasonic vibration Abu-Zahra and Lange (2002). In the cutting region, the acoustic emission stress waves generated are distorted by transmission path and measurement systems and it’s difficult to obtain accurate classification from processing the raw acoustics emission data. Sound signals are frequently used in fault diagnosis, though the noise from other sources reduces the accuracy of the sound signals. According to Dimla (2002), Sokolowski (2004), Li, Dong and Venu vinod (2000) vibrations contain relevant data about wear. Blunt tools generate vibration signals which are different from the vibration signal affected by noises in the machining shop.

The second stage of tool condition monitoring is to extract useful and important features from the signals and take meaningful decision based on the extracted features. In this case Fast Fourier Transform doesn’t give satisfactory results; therefore, there is a need for sophisticated signal processing techniques. Sophisticated techniques require a lot of time and large processing power and speed.

Therefore, there is a need for a technique which does not require much processing power and time. This motivated M. Elangovan et al. (2011) to use principle component and C4.5 for tool wear classification. Jantunen (2002), used statistical features along with time signals for diagnosis of tool wear and signal analysis.

The third Stage involves the use of diagnostic tools for the classification of acquired and processed vibration signals. A good diagnostic tool will have higher accuracy in identifying tool wear. Currently, there are many algorithms with their own history of success and failure.

Sugumaran et al. (2007) used J48 (decision tree) classifier which uses Entropy for classification. Another classifier that uses Entropy is K-star classifier. Saindhya Painuli, M. Elangovan, V. Sugumaran (2014) used K.-star algorithm for classification and got effective classification accuracy. NNge is a rule-based classifier and its performance has never been reported in literature for tool condition monitoring. Sriram et al. (2015) used NNge classifier and K-star to classify whether a person is suffering from Parkinson's disease or not using voice signals. Alok Kumar (2017) analysed the performance of all rule-based classifier and found that NNge had the best accuracy among other rule-based classifier. A good computation accuracy using rule based classifier can be useful in determining the severity of defect. This further motivated the use of NNge as a classifier.

This experiment follows the footsteps of Rao (1986), Saindhya Painuli et al. (2014) in taking the experimental condition as good, Tool blunt mild, Tool blunt severe and tooltip loose. These conditions are discussed in detail in the experimental studies.

This study aims to exploit the vibration signal for monitoring tool health. Descriptive statistical features were obtained from the raw signal as done by Saindhya Painuli et al. (2014). NNge classification was used to build a model to classify tool condition using these statistical features. The response of the classification accuracy is analysed.

EXPERIMENTAL SETUP

The experimental setup is identical to the one used by Saindhya Painuli et al. (2014). It is explained in detail below.

The experiment is carried out with 4 carbide tool TNMG160408. CNC lathe was used with the spindle speed of 600 rpm, depth of cut 0.5mm and feed rate of 0.1mm/s. A piezoelectric accelerometer was used to record these signals on a computer. A pneumatically operated chuck was used to hold a shaft of 20mm diameter. The sensor was (mono axial piezoelectric accelerometer) held in position by adhesive. Then DACTRAN was used to condition the signal and remove any unwanted noise which may be present. Then the acquired signals were recorded by RT-Pro software. These signals were processed to get the statistical features.

This experiment was carried out for different fault condition

- The tool tip is good (Good)
- The tool tip is slightly blunt (TBL1) 0.3mm.
- The tool tip is highly blunt (TBL2) 0.6mm.
- The tool tip is loose (TTL) by one-twelfth of revolution.

SIGNAL ACQUISITION

A new carbide tool TNMG160408 (cutting tool) is placed and secured in the tool post. The mono axial piezoelectric accelerometer is fixed on the tool holder using an adhesive. Nyquist sampling theorem states that "A band limited continuous signal can be sampled and perfectly reconstructed from its sample if the waveform is sampled over twice as the highest frequency component". The sample frequency was taken as 24kHz as the highest observed frequency was 12kHz. The sample length was 8192. Rough turning was carried out to remove the oxidation layer to ensure the smooth surface of the rod. Signal acquisition was started after a delay of one minute to avoid random measurement at the start of the experiment. The experimental setup recorded around two hundred signals. This experiment was repeated for different tool conditions keeping the sample length and sample frequency constant.

FEATURE EXTRACTION

Statistical tools are applied to the vibration signals to get statistical features. Microsoft Excel is used to obtain statistical features in this paper. The macro code used to obtain the statistical feature is given for reference in Figure 1.

The raw signal is first saved in ‘txt’ format. This ‘txt’ file is in the excel sheet and saved. Now create a macro enabled file and create a new macro to extract the statistical features. For brief information of the statistical feature refer Saindhya Painuli et al. (2014)

```
Sub Macro4()
'
' Macro4 Macro
'

'
For i = 1 To 100
    Workbooks.OpenText Filename:="D:\tool_data\GOOD\input1(t) " & i & ".txt", Origin:= _
        1251, StartRow:=1, DataType:=xlDelimited, TextQualifier:=xlDoubleQuote, _
        ConsecutiveDelimiter:=False, Tab:=True, Semicolon:=False, Comma:=False _
        , Space:=False, Other:=False, FieldInfo:=Array(1, 1), _
        TrailingMinusNumbers:=True
     Application.Run "ATPVBAEN.XLAM!Descr", ActiveSheet.Range("$A:$A"), "", "C" _
        , False, True
    Range("B3:B15").Select
    Selection.Copy
    Windows("Book1").Activate
    Range("A" & i & "").Select
    Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
        :=False, Transpose:=True
    Windows("input1(t) " & i & ".txt").Activate
    ActiveWindow.Close
Next i
End Sub
```

Figure 1: Macro Code

CLASSIFIER

The Nearest neighbour based algorithm is the simplest of all instance-based learning algorithms. It stores the entire training set of data in memory for computation at run time. The nearest neighbour classifies the new instances as based on that of its nearest neighbour. Similarly, NNGE classifies the new instances by identifying the closest exemplar using a modified Euclidean distance from hyper-rectangles. During generalisation NNGE considers all instances to be equal, so any rogue instance that might pop up may disrupt the generalisation process. It maintains the classification records for all stored instances in the memory. The instances with a good classifying record are used in the successive classification. It does not remove the poor classifiers; hence it does not provide any storage benefit which is available in IB3 classifier. The classification records modify the similarity between the two. The poor classifiers make it difficult for any exemplars to have any effect on the classification due to it increasing the distance between two exemplars.

The modifications to Euclidean distance allows correct computation of distances from hyper-rectangles. The distance between two continuous points is the difference in values, divided by the range of possible values. This prevents it from favouring attributes with a smaller range over attributed with a large range. NNGE ignores missing attribute values. Even if either the exemplar or hyper-rectangle contained the missing attributes it is skipped and is not counted towards the distance function. At the end, distance function is divided by the number of non-missing values.

CLASSIFICATION BY NNGE

The NNGE classifies the new instance using a modified Euclidean distance function and then determines the closest instance in the hyper rectangular database. Yunling Wang (2004) gave the function as

$$D=W_H\times\sqrt{\sum_{i=1}^{m}(W_i\frac{J_i-K_i}{max_i-min_i})^2}$$

Where J_i is the i^{th} feature value of the instance, K_i is the i^{th} feature value in the exemplar, and W_H and W_i are exemplar and feature weights. The feature difference J_i–K_i for non-generalised hyper-rectangle is given by the difference between a value of the example and exemplar, whereas in the case of generalised hyper-rectangles it is given by

$$J_i - K_i = \begin{cases} J_i - K_{upper}, when\ J_i > K_{upper} \\ K_{lower} - J_i, when\ J_i < K_{lower} \\ 0, \quad otherwise \end{cases}$$

Where K_{upper} and K_{lower} are the boundaries of the hyper rectangle for the feature, after computing the distance between the new instance and all existing exemplar or hyper rectangle. NNGE compares all the classes and chooses the closest one. If there are more than one class, then it chooses the one with the smallest distance and classifies it.

The pseudocode for NNge classifier is given below as given by Yunlig (2004):

PSEUDOCODE OF NNGE CLASSIFIER

While(more examples)

read example

store example

adjust attribute range

Classify Example

while (more rectangles)

compute the distance from new example to rectangle

if(distance < mm distance so far for this rectangle's class

set class minimum distance to this distance

set class count to 1

if (distance = mm distance so far for this rectangle's class)

increment class count by 1

while(more ungeneralised exemplars)

compute the distance from new example to exemplar

if(distance < mm distance so far for this exemplars's class

set class minimum distance to this distance

set class count to 1

if (distance = mm distance so far for this exemplar's class)

increment class count by 1

return class with lowest distance and highest cout

return first exemplar/hyperrectangle found with this class/distance

Adjust Model

if (correct prediction)

increment positive count for this exemplar/hyperrectangle

else

increment negative count for this exemplar / hyperrectangles

if (exemplar falls inside a hyperrectangle of another class)

prune this overgeneralised hyperrectangle

else

adjust weights for attributes with differing values

Generalise the New Example

If (nearest neighbor was hyperrectangle)

extend each feature range to include the new example

if (extended rectangle covers conflicting examples/rectangles)

restore hyperrectangle to original size

store the new example verbatim

else

retain modifications to the hyperrectangle

discard example

if (nearest neighbour was a single example)

create a hyperrectangle that covers the two examples

if (new rectangles that covers the two examples/rectangles)

discard the new hyperrectangle

store the new example verbatim

else

retain the new hyperrectangle

discard example

GENERALISATION

NNGE classifies by generalising the new instance to the nearest neighbour of the same class. In case the instance cannot be generalised then the instance is skipped. In NNGE, the limits of the values of the features stored in hyper rectangles are determined by the maximum and minimum values of its continuous features. Hence, to add a new instance to the new list the maximum values are increased and the minimum value is decreased to include the new instance value.

RESULTS AND DISCUSSIONS

The categorization of tool health is done using NNge classifier and using training dataset to get high accuracy. The vibration signals were recorded for four different conditions (good, TBL1, TBL2, TTL) with 200 readings for each. Since, not all the statistical features extracted from the signal will contain relevant information, these irrelevant data decreases the

accuracy of the classifier. Applying the dimension reduction to the data set, all the irrelevant data is removed. This reduces the processing time and provides greater accuracy. Hence, applying dimension reduction to the 200 readings per tool condition, it was reduced to 100 readings per tool condition. Applyingthe decision tree (J48) classifier to the dataset after dimension reduction and using trainingdataset as test condition gives an accuracy of 97.5 %. The same dataset when using NNge classifier givest classification accuracy of 100 %. The confusion matrix for decision tree is given Table 1 and confusion matrix for NNge classifier is given in Table 2. Quality of the model is judged by the value of True Positive(TP) rate and False Positive (FP) rate. Hence, for a model to be accurate te TP rate has to be almost 1 and FP rate should be almost 0. As Table 3 shows the TP rates are 1 and FP rates are 0, strongly support and validate that this model is correct and can be used to diagnose tool health with 100 % accuracy.

Table 1: Confusion Matrix of Decision Tree Classifier

a	b	c	d	Classiefied as
100	0	0	0	A = Good
0	93	6	1	B = TBL1
0	1	98	1	C = TBL2
0	1	0	99	D = TTL

Table 2: Confusion Matrix of Nnge Classifier

a	b	c	d	Classiefied as
100	0	0	0	a=Good
0	100	0	0	b=TBL1
0	0	100	0	c=TBL2
0	0	0	100	d=TTL

Table 3: Detailed Accuracy Matrix

	TP Rate	FP Rate	Precision	Recall	F-Meausre	MCC	ROC Area	PRC Area	Class
	1	0	1	1	1	1	1	1	Good
	1	0	1	1	1	1	1	1	TBL1
	1	0	1	1	1	1	1	1	TBL2
	1	0	1	1	1	1	1	1	TTL
Weighted Average	1	0	1	1	1	1	1	1	

CONCLUSIONS

This paper provides a method to predict the tool condition using NNge classifier. The use of training dataset ensured an accurate datamodel. Efforts were made to ensure to make an accurate model which could be used even by small scale industries withminimum resources. The classifier providedan accuracy of 100 % for the mentioned cutting parameters (feed rate 0.1 mm/s, Depth of cut 0.5 mm and speed 600 rpm and simulates tool fault condition. Future research can focus on combining two existing algorithms to get better classification accuracy for different test conditions. NNge is not widely reported in the field of tool condition monitoring and it needs to be attempted to fully understand the capabilities of this algorithm.

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